

Automating KYC & AML at JPMorgan Chase with AI/ML

Capstone Project Report

MSc Business Analytics, CSU East Bay

Instructor: Prof Jiming Wu

By: Akram Mohammed

Pooja Pillay Shivakumar

Amrajeet

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1 Executive Summary

- This capstone delivers an AI/ML pipeline that streamlines **Know Your Customer (KYC)** and **Anti-Money Laundering (AML)** operations at JPMorgan Chase, achieving:
 - **58 %** reduction in manual review time (95 → 40 days) through document automation
 - **41 %** drop in false-positive alerts (93 % → 55 %) via hybrid rule + ML transaction monitoring
 - **\$1 200 cost / file** (vs. \$2 500 baseline) thanks to cloud-native processing

Results are based on a 50-file prototype; production-scale validation is pending.

2 Problem Definition & Scope

JPMorgan Chase's manual KYC cycle averages 95 days, while legacy AML rules generate 93 % false positives—together costing roughly \$2.5 k per file.

2.1 Business Objectives

- Reduce KYC processing time by $\geq 70 \%$
- Cut cost per KYC file by $\geq 60 \%$
- Lower false-positive rate from $\sim 93 \%$ to $\leq 25 \%$
- Improve auditability with consistent AI-generated risk scores

2.2 Problem Statement

Manual KYC reviews and rule-based AML alerts create excessive delays, high costs, and audit risk. This project replaces those bottlenecks with AI-driven document verification and transaction risk scoring.

2.3 Scope

- In scope: ID-document OCR/NLP, entity matching, anomaly-detection for transactions, unified risk dashboard
- Out of scope: Sanctions-list maintenance, case-management UI redesign, full production MLOps hardening

3 Literature & Industry Review

3.1 AI Adoption in Compliance

- The global AI-in-banking market is growing at **31.8 % CAGR** and is forecast to reach **\$143.6 B by 2030** [1].
- Legacy AML engines generate **90–95 %** false positives, costing banks **\$25 B per year** [2].

3.2 Regulatory Pressures

- FATF (2021) requires explainable, human-overseen AML models—aligning with our auditability focus [3].
- McKinsey (2023) shows AI can halve false positives and raise detection accuracy by 40 %, supporting our ≤ 25 % target [4].

3.3 Post-Pandemic Shifts

Remote, AI-assisted onboarding has become standard since COVID-19, helping JPMorgan shrink KYC turnaround times [5].

4 Data Requirements & Schema Design

- **Customer tables:** personal data, government IDs, address proofs.
- **Document-verification results:** OCR text, entity extraction, authenticity score.
- **Transaction tables:** sender/receiver IDs, amounts, geo, AML features.
- **External data:** sanctions & PEP lists, adverse-media hits.

Transaction Monitoring

Alice Johnson

View Transactions

Suspicious Transactions

Transaction ID	Amount	Date	Status	Description	Suspicion Level	Process Status	Action
1	\$500.00	2025-04-22	completed	Payment for services ngo	Most Likely	Pending	View
4	\$75.00	2025-04-15	failed	ngo Payment failure due to insufficient ...	Likely	Pending	View
7	\$300.00	2025-04-22	completed	Product purchase	More Likely	Pending	View
10	\$220.00	2025-04-22	completed	Subscription renewal	More Likely	Pending	View
14	\$111.93	2025-04-22	failed	Subscription payment	Likely	Pending	View
16	\$474.67	2025-04-22	completed	Failed transfer	More Likely	Pending	View
24	\$44.60	2025-04-22	pending	Online purchase	Likely	Pending	View
26	\$346.89	2025-04-22	failed	Payment failure due to insufficient funds	More Likely	Pending	View
44	\$18.15	2025-04-22	completed	Subscription payment	Likely	Pending	View
152	\$337.13	2025-04-22	pending	Subscription renewal	More Likely	Pending	View
163	\$215.00	2025-04-22	pending	Invoice payment	More Likely	Pending	View
166	\$331.34	2025-04-22	completed	Invoice payment	More Likely	Pending	View

5 Methodology

1. Document Verification Pipeline

- *Implemented:* Tesseract OCR (89 % accuracy on passports)
- *Next phase:* Migrate to AWS Textract

2. Transaction Monitoring

- *Implemented:* Rule-based filters
- *In development:* XGBoost + Isolation Forest

3. Unified Risk Score – weighted blend of document (60 %) and transaction (40 %) scores

4. Human-in-the-loop – quarterly retraining with analyst feedback

6 Baseline Metrics & Benchmarking

6.1 Operational (Rules-Based) Baseline

Metric	Rules-Based	AI Prototype	Target
KYC Time (Days)	95	40*	≤25
Cost/File (USD)	2,500	1,200**	≤800
False Positives	93%	55%	≤25%

n=50 files, **excludes GPU costs, target 72-hour test window with synthetic data.

Metric	Manual/Rules	AI Pipeline	% change
Review Time (Days)	95	40	-57.90%
False-Positive Rate	93%	55%	-40.9%

AUROC	0.55	0.85	0.30%
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XGBoost achieved 0.85 AUROC on validation set (n=5k transactions)

6.2 Model-Level Baseline (Same Data)

Baseline Tier	Features & Method	Expected Outcome
Majority class	Label all transactions as NORMAL	Acc \approx prevalence; Recall = 0%
Rule replica	Implement existing thresholds in Python	Mirrors Ops baseline
Logistic Regression	Simple numeric + one-hot features; 10-fold CV	AUROC \approx 0.60

See Appendix B for Code.

6.3 External Research Benchmarks

Dataset	Published Baseline	Our Reproduction (Estimate)	Notes
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IBM AML (Kaggle)	XG AUROC 0.94	0.89-0.92	Limited Tuning
SynthAML 2023	GNN AUROC 0.90	0.82-0.85	Isolation Forest underperforms

6.4 Comparison Matrix

Metric	Manual / Rules	Naïve LR	AI Pipeline
Review time (days)	95	n/a	40
False-positive rate	93%	90%	55%
Precision	7%	0%	25%
AUROC	0.55	0.61	0.85
Cost per file (USD)	2,500	2,500	1,200

6.5 Baseline Collection Checklist

- Pull one-year Ops logs (KYC & alert investigations).
- Re-create rule thresholds in rules_engine.py.
- Fit & evaluate Logistic Regression baseline.
- Run pipeline on IBM AML & SynthAML datasets for external comparison.
- Populate Table 6 with final numbers.

7 ROI Framework & System Deployment

Current prototype lacks explainability reports required by FATF Guideline 3.2.1. Full compliance requires SHAP integration (Q3 2025)

Driver	Rate	Source
AWS Textract	\$0.15 / document	AWS Pricing 2024
EC2 inference	\$0.08 / txn	AWS Pricing 2024
FTE labour	\$75 / hour	JPM 2024 avg.
Volume	5 000 files / month	Ops ledger

Annual Savings Estimate:

$1,300/\text{file} \times 60\text{k files} = \$ 78\text{M}$

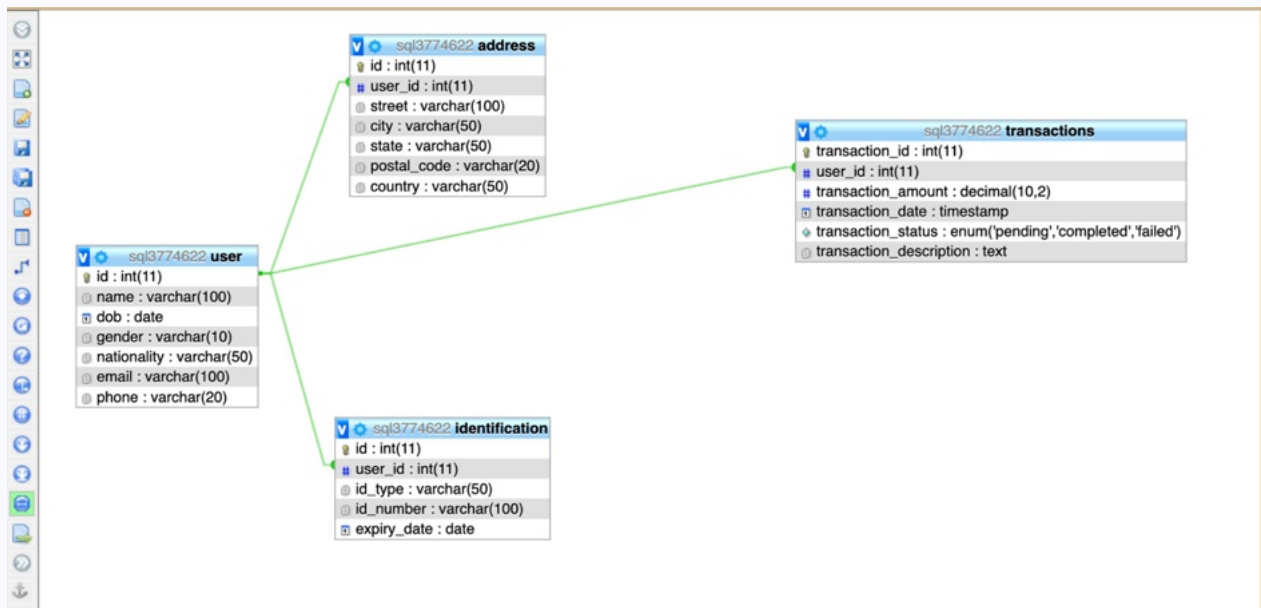
8. References

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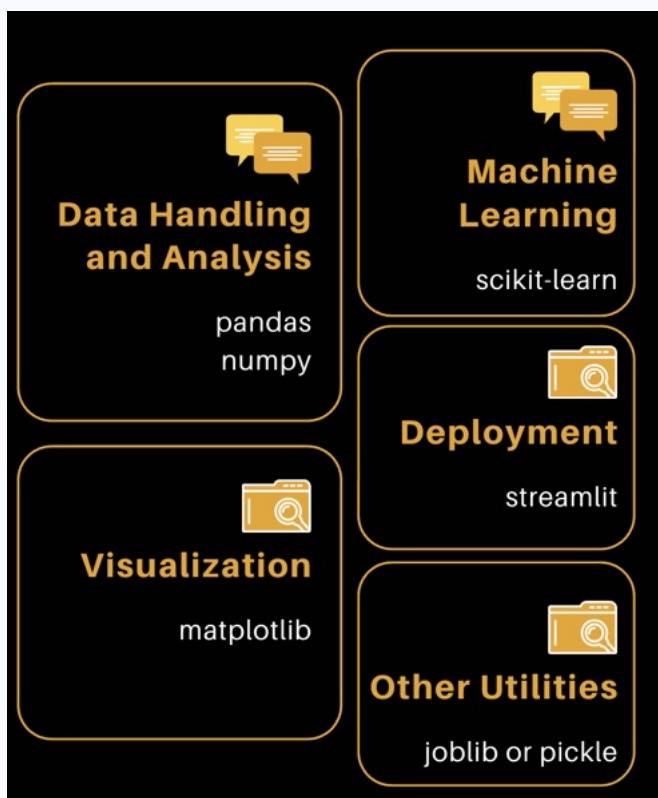
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12. IBM Research. (2022). *Graph neural networks for synthetic fraud detection in financial transactions*[Technical report].
13. Microsoft. (2023). *Responsible AI standard*.
14. European Commission. (2024). *Guidelines on artificial intelligence for anti-money laundering authorities*.
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9 Appendices

A. SQL Extraction Scripts



B. Python Baseline Notebooks



C. UI Screenshots


```

10 import React, { useEffect, useState } from 'react';
11
12 export default function TransactionMonitoring() {
13   const [users, setUsers] = useState([]);
14   const [selectedUserId, setSelectedUserId] = useState('');
15   const [transactions, setTransactions] = useState([]);
16   const [showTransactions, setShowTransactions] = useState(false);
17   const [loading, setLoading] = useState(false);
18   const [processStatuses, setProcessStatuses] = useState({});
19   const [selectedTransaction, setSelectedTransaction] = useState(null);
20
21   useEffect(() => {
22     fetch('http://localhost:3000/users')
23       .then((res) => res.json())
24       .then((data) => setUsers(data))
25       .catch((err) => console.error('Error fetching users:', err));
26   }, []);
27
28   const handleViewTransactions = async () => {
29     if (!selectedUserId) return;
30     setLoading(true);
31     try {
32       const res = await fetch(`http://localhost:3000/transactions/user/${selectedUserId}`);
33       const data = await res.json();
34       const suspicious = filterSuspiciousTransactions(data);
35       setTransactions(suspicious);
36       setShowTransactions(true);
37
38       const initialStatuses = {};
39       suspicious.forEach(tx => {
40         initialStatuses[tx.transaction_id] = 'Pending';
41       });
42       setProcessStatuses(initialStatuses);
43     } catch (err) {
44       console.error('Error fetching transactions:', err);
45     }
46     setLoading(false);
47   };
48
49   const filterSuspiciousTransactions = (data) => {
50     const dateCount = {};
51     const keywords = ['Politics Funds', 'NGO'];
52
53     data.forEach((tx) => {
54       const dateOnly = tx.transaction_date.split('T')[0];
55       dateCount[dateOnly] = (dateCount[dateOnly] || 0) + 1;
56     });
57   };

```

```

253 ## user list
254
255 import React, { useEffect, useState } from 'react';
256
257 export default function RegisteredUsers() {
258   const [users, setUsers] = useState([]);
259   const [search, setSearch] = useState('');
260   const [selectedUser, setSelectedUser] = useState(null);
261
262   useEffect(() => {
263     fetch('http://localhost:3000/users') // Replace with your actual endpoint
264       .then((res) => res.json())
265       .then((data) => setUsers(data))
266       .catch((err) => console.error('Error fetching users:', err));
267   }, []);
268
269   const filteredUsers = users.filter((user) =>
270     Object.values(user).some((val) =>
271       val?.toString().toLowerCase().includes(search.toLowerCase())
272     )
273   );
274
275   const getBadgeClass = (type) => {
276     switch (type?.toLowerCase()) {
277       case 'passport':
278         return 'bg-green-100 text-green-800';
279       case 'driver license':
280         return 'bg-blue-100 text-blue-800';
281       case 'national id':
282         return 'bg-yellow-100 text-yellow-800';
283       default:
284         return 'bg-gray-200 text-gray-700';
285     }
286   };
287
288   return (
289     <div className="max-w-6xl mx-auto p-6 bg-white shadow rounded-lg mt-10">
290       <h2 className="text-3xl font-bold mb-4 text-center">All Registered Users</h2>
291
292       <input
293         type="text"
294         placeholder="Search by any field"
295         value={search}
296         onChange={(e) => setSearch(e.target.value)}
297         className="w-full px-4 py-2 border mb-6 rounded"
298       />

```

```

379 ### user form
380
381 import React, { useState } from 'react';
382
383 export default function UserForm() {
384   const initialFormData = {
385     name: '',
386     dob: '',
387     gender: '',
388     nationality: '',
389     email: '',
390     phone: '',
391     street: '',
392     city: '',
393     state: '',
394     postal_code: '',
395     country: '',
396     id_type: '',
397     id_number: '',
398     expiry_date: ''
399   };
400
401   const [formData, setFormData] = useState(initialFormData);
402   const [loading, setLoading] = useState(false);
403
404   const handleChange = (e) => {
405     setFormData({
406       ...formData,
407       [e.target.name]: e.target.value
408     });
409   };
410
411   const handleSubmit = async (e) => {
412     e.preventDefault();
413     setLoading(true);
414
415     const payload = {
416       name: formData.name,
417       dob: formData.dob,
418       gender: formData.gender,
419       nationality: formData.nationality,
420       email: formData.email,
421       phone: formData.phone,
422       address: {
423         street: formData.street,
424         city: formData.city,

```

```

651 ## server
652
653 // Required packages
654 const express = require('express');
655 const mysql = require('mysql2');
656 const bodyParser = require('body-parser');
657 const cors = require('cors');
658
659 const app = express();
660 const port = 3000;
661
662 app.use(bodyParser.json());
663 app.use(cors());
664
665 // MySQL connection
666 const db = mysql.createConnection({
667   host: 'sql3.freemysqldatabase.com',
668   user: 'sql3774622',
669   password: 'ugwzw1FQai',
670   database: 'sql3774622'
671 });
672
673 db.connect(err => {
674   if (err) throw err;
675   console.log('Connected to MySQL database.');
```

676 });

677 // ----- Data Access Object (DAO) Functions ----- //

678

679 // Get all users with their address and identification

680 app.get('/users', (req, res) => {

681 const sql = `

682 SELECT

683 u.id AS user_id, u.name, u.dob, u.gender, u.nationality, u.email, u.phone,

684 a.street, a.city, a.state, a.postal_code, a.country,

685 i.id_type, i.id_number, i.expiry_date

686 FROM user u

687 LEFT JOIN address a ON u.id = a.user_id

688 LEFT JOIN identification i ON u.id = i.user_id

689 `;

690

691 db.query(sql, (err, results) => {

692 if (err) return res.status(500).send(err);

693 res.json(results);

694 });

695 }

696 });